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Artificial Intelligence, Social Capital, and Sustainable Employment in Peripheral SMEs: A Biocultural Reading from Eastern Macedonia and Thrace, Greece

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Abstract

The accelerating diffusion of artificial intelligence (AI) in Europe raises pressing distributional questions about employment, social cohesion, and sustainable development in disadvantaged regions. Research has concentrated on advanced urban economies, leaving the implications of AI for peripheral small and medium-sized enterprises (SMEs) operating under weak human capital, thin digital infrastructure, and constrained social capital, underexplored. We examine the interplay between AI adoption, social capital formation, workforce dynamics, and sustainable development in Eastern Macedonia and Thrace (EMT), one of the EU's least developed regions. Regional unemployment and educational-attainment data from Eurostat and ELSTAT are incorporated as contextual evidence anchoring the qualitative findings. Drawing on Bitsani's Biocultural City framework which treats human, social, and cultural capital as interdependent dimensions of regional sustainability, we thematically analysed twelve semi-structured interviews with SME owners and managers conducted in early 2025 using Atlas.ti, yielding 19 codes grouped into six categories. Knowledge deficits and financial constraints emerge as primary barriers, while external technology partnerships, targeted education, and economic incentives operate as enablers, all mediated by social and human capital availability. Read through this framework, AI adoption in peripheral economies emerges less as a purely technological or financial challenge than as a social and human capital one, embedded in a biocultural environment shaped by brain drain, institutional thinness, and weak civic intermediation. Without parallel investment in digital literacy, organizational culture, and inter-firm networks, AI risks reproducing rather than reducing employment inequalities. The study draws policy implications for EU Cohesion programming and Sustainable Development Goals 4, 8, 9, 10, and 17.



Academic Editor: Mário José Baptista Franco

Received: 2 May 2026

Revised: 3 July 2026

Accepted: 6 July 2026

Published: 13 July 2026

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Keywords: artificial intelligence; SMEs; social capital; sustainable employment; peripheral regions; digital transformation; brain drain; EU Cohesion Policy; qualitative research; Eastern Macedonia and Thrace, Greece

1. Introduction

Artificial intelligence has changed a great deal over the past few decades, and so has the way we define and use it across economic and social life. Today's systems rest on

artificial neural networks and deep learning. They drive everything from voice assistants and self-driving cars to medical diagnostics and financial analytics, and they have changed how organizations make decisions and deal with employees and customers [1]. Chatbots, general-purpose AI systems, and robotics have already reshaped whole industries. In several narrow tasks, AI now processes data and computes at a level beyond human performance [2].

For SMEs, these developments carry immediate strategic significance. AI adoption can enhance productivity, automate routine processes, and improve data-driven decision-making, thereby supporting innovation and competitiveness [3]. The Fourth Industrial Revolution has intensified pressure on smaller businesses to digitize and embrace technological innovation [4]. AI tools can increase productivity, improve product and service quality, and enhance customer experience in ways that directly shape competitive positioning [5,6]. Automation and data-driven decision support are now accessible without dedicated IT infrastructure, alleviating the resource constraints that define the SME operating environment [7]. The COVID-19 pandemic accelerated this shift, positioning AI-enabled operational flexibility as a strategic necessity [8].

Despite the practical urgency, significant empirical gaps persist. The literature on AI adoption in SMEs has largely focused on technologically advanced urban economies, leaving peripheral regions of Europe, characterized by weak institutional infrastructure, high unemployment, and constrained human capital, almost entirely uncharted [9,10]. This spatial blind spot matters: the dynamics of AI adoption in disadvantaged regions are unlikely to mirror those documented in core economies, and the social and employment consequences may be qualitatively different. The gap is particularly acute for Mediterranean peripheries, where brain drain, institutional dependency, and weak civic intermediation shape adoption trajectories in ways that general models of regional innovation systems do not adequately capture. Bitsani's [11] Biocultural City framework, which theorizes human, social, and cultural capital as interdependent dimensions of Mediterranean urban and regional sustainability, provides the theoretical lens through which the present study reads the AI adoption landscape in one such region.

This study addresses the identified gaps through primary qualitative data from the region of Eastern Macedonia and Thrace in Greece, employing a qualitative design based on semi-structured interviews conducted in early 2025 with SME owners and managers. Three research questions orient the investigation: (RQ1) What factors influence the acceptance and application of AI by SMEs? (RQ2) How can SMEs overcome barriers to AI adoption? (RQ3) What are the best practices for integrating AI into the development strategies of SMEs?

Eastern Macedonia and Thrace (EMT) in Greece constitutes an analytically significant case for examining AI adoption in peripheral regions. The region is consistently among the least developed regions in the European Union, with a GDP per capita (PPS) equivalent to 45% of the EU27 average [12]. EMT exhibits persistent labour market disadvantages, including a regional unemployment rate of 12.1%, a youth unemployment rate of 34.6%, almost twice the EU average of 18.4%, and a long-term unemployment share accounting for 71.8% of total unemployment [13–15]. Human capital constraints are equally pronounced: only 27% of the economically active population holds tertiary qualifications, compared with the national average of 35%, while the region's higher education sector has experienced a 38% decline in researcher headcount since 2013, reflecting persistent brain drain and a weakening regional knowledge base [15]. These structural challenges are compounded by the region's strategic geopolitical location and an economic structure concentrated in traditional sectors characterised by relatively low levels of digitalisation and knowledge-intensive activity, particularly agriculture and wholesale and retail trade [15]. Collectively, these characteristics make EMT a highly relevant empirical setting for investigating AI

adoption under conditions of peripheral fragility, with important implications for EU Cohesion Policy and the achievement of Sustainable Development Goals (SDGs) 4, 8, 9, 10, and 17.

2. Literature Review

2.1. Background and Context

The acceleration of AI adoption across industries reflects the convergence of sustained advances in machine learning, the democratization of open-source toolkits, improvements in data infrastructure, and a pronounced decline in hardware costs and specialist labour requirements. Cloud-based platforms have further lowered the entry threshold for organizations of all sizes, enabling rapid scaling of AI capabilities without commensurate capital expenditure [16]. Absorptive capacity theory [17] provides an important analytical lens for understanding how SMEs vary in their ability to identify, assimilate, and exploit externally available AI knowledge, a capacity strongly conditioned by prior related knowledge and internal technical expertise.

2.2. Social Capital, Human Capital, and AI Adoption: A Biocultural Reading

The concept of social capital, encompassing the networks of trust, reciprocity, and cooperation through which actors access resources, has been extensively theorized as a determinant of innovation diffusion and organizational learning [18–20]. In the context of AI adoption, social capital operates at multiple levels. At the inter-firm level, bridging social capital, connections between SMEs and external technology providers, business associations, and public agencies, constitutes a primary mechanism through which peripheral firms access knowledge, finance, and legitimacy for AI integration. At the intra-firm level, bonding social capital, the quality of internal networks and shared norms, shapes organizational receptivity to technological change [21].

The spatial dimension of social capital is particularly salient for peripheral regions. Harvey's [9] analysis of uneven geographical development demonstrates that technological diffusion reproduces spatial inequalities when it follows the path of existing capital and knowledge concentrations. Tödtling and Trippel [10] identify thin regional innovation systems, characterized by weak inter-firm linkages, limited R&D infrastructure, and scarce knowledge-intensive services, as a defining feature of peripheral economies, and document their constraining effect on technology adoption. In such contexts, the knowledge deficits and dependency on external partnerships that characterize AI adoption express peripheral disadvantage at a structural level.

This reading of structural disadvantage is specified more concretely by Bitsani's [11] Biocultural City framework, which theorizes how Mediterranean peripheral territories reproduce or transform inequalities through the differential mobilization of cultural, social, and human capital. The framework treats these three forms of capital not as parallel resources but as interdependent dimensions of a single biocultural environment: civic trust, knowledge circulation, educational endowment, and cultural continuity jointly shape the conditions under which technological and institutional change becomes possible. Applied to AI adoption in peripheral settings, the framework identifies thin institutional intermediation and weak inter-firm networks as expressions of a depleted enabling infrastructure, not as isolated organizational deficiencies. It offers a theoretically grounded explanation for why AI adoption barriers in Mediterranean peripheries tend to be more intractable than in non-Mediterranean peripheral economies: the cumulative erosion of human capital through brain drain and of bonding social capital through decades of out-migration has left the regional enabling infrastructure too depleted to convert external technology and funding into sustained adoption.

Human capital, the skills, competencies, and educational endowments of the workforce, shapes AI adoption capacity directly. In Mediterranean peripheral settings, brain drain erodes human capital and, with it, the bonding social capital that holds local inter-firm trust together. The two losses overlap. Financial incentives, technology provision, or training programs cannot repair them one at a time [11]. This dynamic recasts the deskilling versus upskilling debate [22]. Peripheral SME workforces are weighted toward routine-task roles most exposed to automation, while the best-educated workers have already left the regional labour market [23]. The internal talent pool shrinks accordingly, and a structural barrier to AI adoption emerges that money alone will not remove. The organizational culture of SME owner-managers, their attitudes toward risk, technology, and change [24,25], grows out of this same environment. In low-trust, low-connectivity regional contexts, risk aversion and technological conservatism represent rational adaptive responses to local conditions, not simply correctable individual failings.

2.3. Review of Previous Research

A decade of research has produced substantial literature on AI adoption, but the evidence is unevenly distributed. Most studies concentrate on large organizations in technologically advanced economies. SMEs in peripheral regions appear rarely, and Mediterranean peripheries scarcely at all. Among the studies most relevant to the present inquiry, Rawashdeh et al. [4] used structural equation modelling to show that accounting automation mediates the relationship between technological readiness and adoption outcomes in SMEs. Their key finding, that SME owners adopt AI chiefly to save time and cut costs rather than to innovate, matters for policy. Framing AI as an innovation driver may miss how these businesses actually think about the technology.

How AI affects workers has attracted more recent attention. Ambati [26] showed that individual attitudes toward AI, and especially perceived usefulness, matter as much as technical capability in explaining uptake. Malik et al. [22] pushed further, drawing on 32 interviews across nine sectors. What they found is worth dwelling on: AI adoption is genuinely double-edged. Workers reported gains in autonomy and performance alongside new anxieties about data security, job stability, and what the authors call technostress. Malik et al. [22] concluded that upskilling must go beyond software training to build communication, critical thinking, and collaborative skills, precisely the capacities that thin peripheral labour markets tend to lack.

The knowledge barrier is well documented but still underestimated. Malin et al. [27] traced the primary obstacle to adoption in HR contexts not to cost or technology, but to practitioners' own confused beliefs about what AI can and cannot do, a finding that resonates directly with what our interviewees told us. On the regulatory side, Ho [28] showed that legal ambiguity around algorithmic governance actively suppresses adoption confidence: firms hesitate not because they distrust the technology but because they distrust the rules governing it. Jang et al. [29] reached similar conclusions in the South Korean financial sector. Even where managers could see the potential of AI-powered chatbots, regulatory uncertainty and knowledge gaps kept adoption at bay.

Two further studies extend the picture in useful directions. Yeo et al. [30] demonstrated that AI-driven personalization shapes consumer behaviour in social commerce in measurable ways, while Livberber and Ayvaz [31] documented the ambivalence of academics toward generative AI, useful for drafting and synthesis but worrying for questions of integrity and attribution. Together these studies confirm one consistent finding: AI adoption is always shaped by context, by the industry, the regulatory setting, the organizational culture. What none of them addresses is the regional and biocultural dimension. How do the specific conditions of Mediterranean peripheral settings (eroded civic trust, depleted

human capital, thin inter-firm networks) shape what adoption is actually possible, and for whom? That is the question this study takes up.

2.4. Research Field Gaps

The review points to three gaps that the present study is positioned to address. First, organizational-level evidence on AI adoption remains thin overall [4,22,29,31,32], and within that already limited body of work, SMEs, let alone SMEs in peripheral regions, are largely absent [4]. Second, the human experience of AI integration, the technostress, the skill anxieties, the job insecurity [22], has been noted but not adequately theorized. Third, and most relevant here, no study in this review reads AI adoption through the lens of biocultural peripheral development. The established frameworks (absorptive capacity [17], TAM [25], Diffusion of Innovations [24]) were built to explain adoption where the necessary enabling conditions already exist. Applied to contexts where those conditions have been systematically eroded, they describe symptoms without explaining causes. No study identified in this review addresses the Greek regional context, leaving the dynamics of AI adoption in Eastern Macedonia and Thrace entirely uncharted. The present study addresses all three gaps.

2.5. Contribution

This research contributes primary empirical data from the Eastern Macedonia and Thrace region, addressing both international literature gaps and regional evidence needs. It advances a biocultural reading of AI adoption barriers, drawing on Bitsani's [11] framework, which reframes knowledge deficits and external dependency as expressions of a cumulative human, social, and cultural capital deficit characteristic of Mediterranean peripheries, and not as organizational failures. The originality of this contribution lies in what it explains rather than in the constructs it employs. The Technology Acceptance Model [25], absorptive capacity theory [17], and regional innovation systems analysis [10] model how adoption proceeds where enabling structures are present. They treat the supply of skills, trust, and institutional intermediation as background conditions. The biocultural framework instead theorizes why those enabling conditions are absent in Mediterranean peripheries, specifying how brain drain and the erosion of civic trust interact to produce a compounded disadvantage that none of these established frameworks captures when applied in isolation. The framework therefore complements rather than replaces TAM and diffusion-of-innovation approaches, extending them to settings where their presumed antecedents do not hold. This reframing shifts the intervention logic from technology provision to the parallel development of the social, human, and institutional infrastructure that makes technology adoption possible and sustainable. The study further contributes to the SDG literature by demonstrating the conditions under which AI can either advance or undermine SDGs 4, 8, 9, 10, and 17 in weak European peripheries.

3. Materials and Methods

3.1. Data Collection

The research followed a sequential qualitative design comprising planning, instrument development, reliability assessment, sample selection, and interview conduct [33]. Semi-structured interviews served as the primary data collection instrument, selected for their capacity to elicit nuanced perceptions of AI adoption barriers and enablers while maintaining sufficient structure to enable cross-case comparison [33–35].

3.2. Data Collection Instrument

A 25-item interview guide was developed inductively from the literature, drawing on Malik et al. [22], Malin et al. [27], and Ho [28], and structured to address six thematic domains: AI understanding and application; business expectations and use cases; learning, innovation, and adaptation; competitive strategy; regulatory framework perceptions; and organizational and workforce impacts.

3.3. Validity and Bias Control

Interview questions were organized to align directly with the study's objectives and research questions [34,36]. Participants received a preparatory briefing explaining the process, addressing confidentiality and anonymity, and confirming their freedom to respond without guidance or censorship. Multiple potential sources of bias were addressed, researcher influence, guide deviation, unequal respondent treatment, and question reformulation [37,38], through uniform question sequencing and refraining from unsolicited intervention. Trustworthiness was pursued across the four criteria established for qualitative research [39]. Credibility was supported by member-checking, in which analytical summaries of the emerging themes were returned to a subset of participants to confirm that the interpretations reflected their intended meaning. Transferability rests on the thick description of the regional and organizational context provided in Sections 1 and 3.4, which lets readers judge the applicability of the findings to other peripheral settings. Dependability was secured through an audit trail documenting all coding and analytical decisions in Atlas.ti, and confirmability through peer debriefing at the theme-generation stage.

3.4. Sample Selection

Twelve businesses from different sectors in Eastern Macedonia and Thrace, Greece, were selected using purposive criterion-based sampling. Four inclusion criteria governed selection: (a) location in the region; (b) SME classification; (c) more than two years of operation; and (d) researcher-assessed plausible capacity to adopt AI technologies. Following Rowley [40], approximately 12 interviews of 30 min each are accepted practice, and Guest et al. [41] confirm that 12 interviews are sufficient for capturing common perceptions within criterion-based purposive samples. Thematic redundancy across the final three interviews confirmed the adequacy of the sample for the defined analytic purpose [42]. The sample was designed for purposive homogeneity, rather than statistical representativeness: the inclusion criteria deliberately narrow the population to peripheral EMT SMEs with plausible AI adoption capacity, producing a sample coherent enough that 12 interviews capture the shared conditions of the target group. Guest et al. [41] demonstrate that in homogeneous purposive samples most core themes emerge within the first six to twelve interviews. The design prioritizes analytical depth over statistical generalizability. The study's inferential logic is accordingly one of analytic, not statistical, generalization [43]: the findings are advanced as theoretically grounded propositions about the conditions under which AI adoption proceeds in a biocultural periphery, transferable to comparable settings as hypotheses for further testing rather than as frequency estimates for the regional SME population. This bounds the epistemic status of the claims developed in the Discussion and Conclusions sections.

3.5. Data Analysis

Data analysis followed the six-stage thematic analysis protocol [34], operationalized through Atlas.ti (version 23; ATLAS.ti Scientific Software GmbH, Berlin, Germany). Stage 1 involved transcription of the 12 recorded interviews into Word files using Otter.ai (version 3.x; Otter.ai, Inc., Mountain View, CA, USA) transcription software. Stage 2 generated

19 initial codes identifying significant data elements through inductive coding, allowing themes to emerge from participant responses rather than being imposed a priori. Stages 3–5 involved theme generation, visual mapping, validity evaluation, and consolidation into six thematic categories. Stage 6 produced the final report, selecting excerpts that evidenced the identified themes. The overall analytical approach combined deductive orientation with inductive openness: while research questions and the biocultural framework shaped the initial coding strategy, emerging themes were allowed to develop from the data itself.

The progression from raw transcript to thematic category proceeded through three explicit analytical movements. First-cycle descriptive coding assigned the 19 inductive codes to data segments. Second-cycle pattern coding then clustered semantically proximate codes. For example, the codes “partial AI comprehension,” “confident AI comprehension,” and “applied AI awareness” were grouped under the category Understanding and Application of AI, while “capital intensity,” “subsidy dependence,” and “return-horizon uncertainty” were consolidated into the financial-constraint dimension of Expectations and Applications. Each candidate category was then tested against the full corpus to confirm that it was grounded in recurrent rather than isolated statements. Table 1 sets out the resulting coding framework, linking each thematic category to its most representative constituent codes and to an anchoring participant quotation. The codes shown are illustrative rather than exhaustive: for each of the six categories the table presents the most indicative of the 19 inductive codes together with a single quotation, while the complete codebook of all 19 codes is retained in the Atlas.ti audit trail described in Section 3.3 and is available from the authors on request. The inferential path from data to interpretation is thereby open to inspection.

Table 1. Coding framework: thematic categories, constituent codes, and representative quotations.

Thematic Category	Constituent Codes (Illustrative)	Representative Quotation
1. Understanding and application of AI	confident comprehension; partial comprehension; applied awareness	“I know it, not exactly” (Int. 6)
2. Expectations and applications of AI in business	capital intensity; subsidy dependence; skills threshold	“the capital needed is significant” (Int. 1)
3. Learning, innovation, and adaptation	time scarcity; data-security concern; professional development	“the lack of available free time” (Int. 1)
4. Strategy and competition	strategic uncertainty; limited market-expansion belief	“I do not think it can help to expand my business” (Int. 4)
5. Regulatory framework	regulatory ambiguity; demand for legal clarity	“There should be a specific legal framework” (Int. 5)
6. Impact on work environment and organizational structure	process improvement; job-substitution risk; decision support	“potential loss of jobs” (Int. 5)

Two procedures were used to assess the trustworthiness of this coding. Sample adequacy was evaluated through an explicit saturation check rather than asserted. The codebook was treated as stable once three successive interviews produced no new codes and no modification to existing category boundaries, a condition reached by the tenth interview, with the final two interviews confirming redundancy [41,42]. Coding valida-

tion followed a dual-coder procedure in which a second member of the research team independently re-coded a randomly selected subset of approximately one third of the transcripts. Coding discrepancies were resolved through consensus discussion, and the few residual disagreements concerned code labelling rather than the assignment of segments to categories. Because the dataset is qualitative and the codebook small, agreement is reported descriptively rather than as a single reliability coefficient, consistent with established guidance on validation in interpretive thematic analysis [39].

3.6. Ethical Considerations

All participants provided written informed consent prior to interview. The study was conducted in accordance with the ethical guidelines of the Democritus University of Thrace. No personally identifiable data are reported, and all participants are referred to by interviewee number only.

4. Results

Thematic analysis generated six categories from the 19 initial codes: 1. Understanding and application of AI; 2. Expectations and applications of AI in business; 3. Learning, innovation, and adaptation; 4. Strategy and competition; 5. Regulatory framework; 6. Impact on the work environment and organizational structure. Each is reported below in descriptive terms, with interpretation deferred to Section 5.

4.1. Understanding and Application of AI

AI comprehension among interviewees ranged from confident to partial or cautious. Several respondents expressed clear awareness (Int. 1: “Yes, to some extent”; Int. 3: “Certainly”; Int. 4: “Of course, I understand it fully”). Others reported more limited or vague understanding (Int. 6: “I know it, not exactly”; Int. 8: “I have heard something”; Int. 12: “Hmm, approximately”). One respondent offered an applied perspective, noting that artificial intelligence “can replace physical labour” (Int. 5) and elaborated on its potential in medical diagnosis.

4.2. Expectations and Applications of AI in Business

Views on AI’s role in improving customer experience varied. Respondents anticipating positive impact cited faster information delivery and more effective query resolution (Int. 5: “Definitely, AI could improve customer knowledge and experience”). Others doubted AI’s contribution to personalized service quality (Int. 1: “[the customer experience] cannot be meaningfully improved through AI”). Capital requirements were identified as disproportionate for small businesses, compounded by knowledge gaps (Int. 1: “Mainly financial. As a small business, the capital needed is significant and the lack of knowledge in managing such applications”). Technological proficiency was also noted as a constraint (Int. 9: “We are not very knowledgeable about computers, but a relatively high level of computer skills and English is required”).

4.3. Learning, Innovation, and Adaptation

Privacy and data security perceptions varied substantially. Some respondents reported no concerns (Int. 1, 2: “None”; “I have no insecurities”). Others expressed specific concern about personal data leakage (Int. 4: “The fact that it is at a relatively early stage, so I mainly fear for the leakage of customers’ personal data”). Principal learning barriers reported were time scarcity (Int. 1: “Certainly the lack of available free time”), limited digital literacy (Int. 9: “We don’t know about computers”), and anticipated customer resistance (Int. 5). Adoption motivators cited were economic, demonstrated production optimization and subsidy-based incentives (Int. 1), competitive development goals (Int. 5), and professional

development imperatives (Int. 11: “Improvement, evolution, professional development in terms of knowledge, technology for every employee, and the need of the time above all”).

4.4. Strategy and Competition

Most interviewees were unable to articulate specific AI-related competitive mechanisms (Int. 1, 3, 12: “I do not know”). One respondent explicitly discounted AI’s current developmental stage as insufficient for market expansion purposes (Int. 4: “at the point it is, I do not think it can help to expand my business in the market”).

4.5. Regulatory Framework

Regulatory ambiguity emerged as a recurrent concern. Multiple respondents anticipated that unclear rules would generate widespread hesitancy within the business community (Int. 3: “probably many will be overwhelmed with fear”), and personal uncertainty was expressed (Int. 6: “There is a bit of concern”). The creation of a clear legal framework was consistently identified as a critical enabler of AI trust (Int. 5: “There should be a specific legal framework on which all this endeavor should be based”; Int. 4: “clear regulatory framework that would help people trust and implement software technologies of artificial intelligence”).

4.6. Impact on the Work Environment and Organizational Structure

AI adoption was anticipated to improve the management and execution of business processes (Int. 1: “better management of resources consumed in the production process”; Int. 4: “faster updates”), while raising concerns about reduced demand for human personnel in certain functions (Int. 5: “potential loss of jobs”). On decision-making, views spanned a broad range: some respondents expected AI to enhance the process substantially through an advisory function, while others believed its contribution would be minimal. Regarding job security, technological progress was seen by some as potentially affecting employee confidence negatively through substitution risk (Int. 5), while others conditioned this on whether AI was deployed to grow the business, in which case it “could be positive for everyone” (Int. 3).

5. Discussion

The findings reveal that AI adoption among SMEs in Eastern Macedonia and Thrace is shaped by a combination of cognitive, financial, regulatory, and behavioural constraints. The three research questions are addressed in turn, with the biocultural framework developed in Section 2.2 providing the interpretive axis. Throughout, claims grounded directly in the interview corpus are kept distinct from interpretations that the biocultural framework extends beyond it: the former are tied to the coded categories of Table 1 and to named interviewees, the latter are identified as framework-level inference and carry the evidential weight of a single-region, twelve-interview design.

5.1. Factors Influencing AI Acceptance (RQ1)

Two factors dominated across the twelve interviews: knowledge deficits and economic constraints. A substantial proportion of entrepreneurs expressed uncertainty or partial understanding of what AI is and how it operates in practice, ranging from surface familiarity (Int. 1, 3, 4) to vague recognition (Int. 6, 8, 12), replicating the pattern of knowledge ambiguity identified by Malin et al. [27] as the primary cognitive brake on AI adoption. Financial and infrastructural barriers compounded this deficit: capital requirements were consistently described as disproportionate for small businesses (Int. 1), while low digital literacy further narrowed the range of accessible tools (Int. 9).

Read through the framework of Section 2.2, these barriers trace back to a weakly developed regional innovation system [10]. Where inter-firm networks are sparse, knowledge-intensive services few, and bridging ties to technology ecosystems scarce, such knowledge deficits follow predictably from the region's structural conditions rather than from any shortcoming of the individual firm. The near-total absence of strategically grounded AI awareness documented in Section 4.4, where most interviewees were unable to articulate specific competitive mechanisms, is consistent with this reading: without access to bridging social capital connecting firms to external knowledge ecosystems, strategic AI thinking cannot develop from within a thin innovation system.

The Biocultural City framework [11] gives this reading a Mediterranean specificity. In these settings, brain drain and the weakening of inter-firm trust networks are not separate stories. Each feeds the other, and the disadvantage builds. The interviews document the knowledge deficits directly (Section 4.1). Reading those deficits as the downstream effect of an earlier exodus of the region's best-educated workers is a framework-level interpretation, anchored in the regional brain-drain indicators of Section 1 rather than established by the twelve interviews on their own. That exodus does two things at once: it thins the talent pool available to SMEs and it wears away the bonding social capital, shared professional norms, peer learning, intra-sector knowledge circulation, through which AI literacy might otherwise grow from inside the business community. Knowledge barriers in EMT are therefore harder to shift than in non-Mediterranean peripheries where brain drain has been milder. It also explains why money spent purely on technology acquisition falls short: the absorptive capacity needed to deploy and sustain AI tools [17] has been drained at both the individual and the network level.

Investment perception points to a time-horizon problem as well. Interviewees repeatedly weighed prohibitive short-term costs against uncertain long-term returns. That calculation grows harsher in peripheral contexts, where credit is hard to obtain, institutional support is thin, and dense inter-firm networks are absent. Seen this way, the risk aversion and technological conservatism of EMT owner-managers (Sections 4.2 and 4.4) read as sensible responses to local conditions, and the distinction matters for how policy is designed (Section 5.2). Secondary barriers, data privacy concerns (Int. 4), regulatory ambiguity (Int. 3, 6), technological complexity (Int. 9), and anticipated customer resistance (Int. 5), echo what Ho [28] and Jang et al. [29] report, and point to the wider institutional uncertainty of regions with weak regulatory intermediation and limited civic-sector capacity.

5.2. Overcoming Adoption Barriers (RQ2)

When interviewees were asked what would make AI adoption possible, external technology partnerships came up first and most consistently. This is not surprising, but it is telling. In a thin innovation system with few bridging ties to knowledge ecosystems, a partnership with an external technology provider is often the only realistic route to AI access [19]. It substitutes, at least temporarily, for the absorptive capacity [17] that brain drain and network atrophy have depleted. The firms are not choosing partnerships strategically; they are choosing them because there is no internal alternative.

There is, however, a problem with partnerships as currently practised. When a technology provider installs a system and leaves, the SME has acquired a tool but not the capacity to use it well, adapt it, or evaluate whether it is actually working. As Bitsani [11] argues, this pattern, external resource provision without local capacity-building, is a known trap in Mediterranean peripheral development: it reinforces the very dependency it appears to relieve. For partnerships to work as enablers rather than as dependency mechanisms, they need to be structured differently: built around co-training, joint problem-solving, and

the deliberate transfer of digital competencies to SME staff. The goal is not to hand over a technology but to leave behind an organization that can continue without the partner.

Education and training were the second enabler interviewees consistently named, and their language was telling: not “useful” or “helpful” but necessary. Int. 11 put it plainly: “improvement, evolution, professional development in terms of knowledge, technology for every employee, and the need of the time above all.” This framing (training as a precondition, not a supplement) is consistent with Malik et al. [22] and reinforces what the biocultural reading of Section 2.2 predicts: the deskilling risk in EMT SMEs comes not from AI itself but from deploying AI without parallel investment in people. Technical training alone is not enough. Evidence from the Greek manufacturing sector confirms that bridging the AI skills gap requires structured networking between educational institutions and businesses, not just updated curricula [44]. In regions where brain drain has attenuated bonding social capital over decades, rebuilding peer learning networks and inter-firm communities of practice is a policy goal in its own right, not something that happens automatically as a side-effect of any individual training programme.

Financial incentives were the third enabler interviewees named, and the reasoning was straightforward: several respondents could see AI’s long-term value but simply could not absorb the upfront cost (Int. 1). This is a structural feature of peripheral SME contexts, not a budgeting failure [23]. But incentives that fund technology acquisition without first ensuring that the organizational and human capital conditions for productive use are in place risk purchasing hardware that sits underused. The three enablers (partnerships, education, and financial support) are not alternative routes to AI adoption. They are interdependent preconditions. Policy instruments that address only one will fall short. The implications for EU Cohesion Policy programming are taken up in Section 5.4.

5.3. Best Practices for AI Integration (RQ3)

The most workable near-term strategy was targeted application: deploying sector-appropriate tools tuned for efficiency and cost reduction. A clear, stable regulatory framework came up repeatedly as a precondition for trust, in line with Ho [28] and Jang et al. [29]. On the employment side, the findings flag a real danger. Without parallel investment in digital literacy and organizational culture, AI adoption in peripheral SMEs of this kind carries a clear risk of widening rather than easing labour-market inequalities. This is a risk projected from interviewee perceptions and the wider literature, not an outcome the present design measures. When respondents named substitution risk (Int. 5), they were pointing to a dynamic well documented in the wider literature: automation tends to displace routine-task workers, and such workers are over-represented in peripheral economies [23]. This pattern is consistent with the skill-biased technological change literature, which shows that technological adoption does not affect workers uniformly but rather rewards those already holding scarce competencies while displacing routine and lower-skilled labour, thereby widening pre-existing wage and employment disparities. Recent evidence on skill-biased technological change and gender wage inequality [45] underscores that these heterogeneous effects fall unevenly across worker groups, a dynamic likely to be amplified in peripheral labour markets where the most qualified workers have already emigrated. The implication for EMT is that AI diffusion absent compensating policy is liable to reproduce the very stratification it is sometimes assumed to dissolve.

Addressing this risk requires linking AI adoption support with active labour market measures, digital upskilling programs calibrated to the DigComp 2.2 framework, and regional economic diversification. Policy design for such upskilling programs must explicitly account for a further dynamic documented in the welfare governance literature: when provision of resources, whether financial support, training, or access to technology, is coupled

with behavioural compliance obligations, the result can be new forms of subjectification instead of the autonomy such programs formally pursue [46]. For AI-focused upskilling in peripheral regions the implication is concrete. Programs that make participation conditional on rigid performance metrics or continuous surveillance of learners may produce compliance without competence, reproducing the dependency that capacity-building programs are designed to resolve.

5.4. Biocultural Reading, Spatial Inequality, and the SDG Agenda

The EMT case makes one point unavoidable: AI adoption here is not primarily a technology problem or a funding problem. It is a social and human capital problem. Knowledge deficits, network atrophy, and dependency on external partners are not isolated failures. Read through the biocultural framework, they are better understood as the outcomes of a regional environment shaped by decades of brain drain, institutional thinness, and weak civic intermediation [11,23], an interpretation anchored in the regional indicators of Section 1 and extending beyond what the twelve interviews measure on their own. Channeling technology and money into this environment, without first addressing its social infrastructure, is unlikely to produce the adoption outcomes that EU Cohesion Policy and the SDG agenda require.

This has direct implications for how EU Cohesion Policy is designed. The standard programmatic package (broadband expansion, hardware subsidies, platform access) is not wrong, but it is insufficient on its own, and in weak peripheral contexts it can actually reproduce the inequalities it is meant to reduce [9,10]. Civic trust, knowledge circulation, inter-firm collaboration: these are not soft add-ons to a digital infrastructure programme. They are the conditions that make digital infrastructure usable. In Mediterranean peripheries they are built slowly, through sustained social and cultural investment, and they cannot be retrofitted after the hardware is already in place [11]. The ESPA 2021–2027 digital transformation priority axis for Less Developed Regions provides one concrete mechanism, but only if co-financing is conditioned on knowledge transfer obligations and partnership frameworks are explicitly designed to build local capacity rather than deliver external solutions. On the reading advanced here, social capital development is better treated as the foundation around which technology and financial instruments are organised than as an optional extra appended when resources permit.

The SDG connections are not decorative. Each barrier documented in the data maps to a specific target. The digital literacy and skills deficits that emerged repeatedly across the twelve interviews are a regional expression of Target 4.4, the failure to equip the workforce with technical and vocational skills for employment. The substitution anxieties interviewees named (Int. 5), the technostress Malik et al. [22] theorize, the exclusion of routine workers from productivity gains: these are Target 8.3 and 8.5 in action, in a labour market where alternatives are scarce and the people most exposed to automation have nowhere else to go. The thinness of the regional innovation ecosystem (weak inter-firm networks, scarce knowledge-intensive services, no functioning technology intermediaries) is precisely the infrastructure gap that Target 9.b addresses. And the compounding of brain drain, low digital literacy, and eroded bonding social capital into a single structural disadvantage is what Target 10.2 looks like at the regional level. The linkages tied to digital skills, unemployment, and educational attainment rest on the measurable regional indicators set out in Section 1. Those involving eroded civic trust and bonding social capital are framework-level inferences, offered as interpretation rather than as measured quantities.

SDG 17, Partnerships for the Goals, is where the dependency dynamic identified in Sections 4.2 and 5.2 becomes most visible as a sustainability problem. The partnerships SDG 17 envisions are built on mutual capacity-building and shared knowledge production.

What EMT SMEs actually experience is something different: a technology provider arrives, installs a system, and leaves. The SME gains a tool; the provider retains the knowledge, the upgrades, and the leverage. This is not partnership in the SDG sense. It is a market transaction that positions peripheral firms as consumers of externally produced solutions rather than agents of locally embedded innovation. Reversing this logic requires that partnership frameworks (whether brokered by regional development agencies, universities, or EU-funded intermediaries) carry explicit knowledge transfer obligations and measurable local capacity-building outcomes. The DigComp 2.2 framework offers a concrete baseline for defining those outcomes in AI literacy terms. More broadly, and as a proposition for testing beyond this single region, the EMT case suggests that AI policy in comparable peripheral regions should be SDG-integrated from the beginning of programme design. Treating the 2030 Agenda as a reporting framework applied after the fact misses the point: the SDGs are constraints on how policy should be designed, not boxes to tick once results are in.

5.5. Limitations

The study's limitations include restricted geographical coverage; findings from Eastern Macedonia and Thrace may not generalize to other Greek regions, other European member states, or non-European SME contexts, where different cultural, economic, and enabling conditions may produce divergent adoption dynamics. Criterion-based purposive sampling may not fully represent the diversity of the regional SME sector. The qualitative design precludes quantitative analysis, statistical correlation, and causal inference. Relatedly, the study documents owner-managers' perceptions of AI-related employment risk, skill gaps, and substitution pressure. It does not measure employment outcomes directly. Job creation, displacement, wage effects, and workforce restructuring lie outside a twelve-interview perceptual design and are identified as priorities for future research in Section 5.6. References to sustainable employment throughout should therefore be read as perception-based and framework-guided rather than as measured labour-market effects. Although the dual-coder validation reported in Section 3.5 strengthens analytical credibility, the small codebook means agreement is documented descriptively rather than through a formal reliability coefficient. Two further sources of bias warrant acknowledgement. Because participation was voluntary and selection favoured firms with plausible AI-adoption capacity, the sample may over-represent owner-managers already disposed toward technology, a selection effect that could understate the depth of resistance in the wider population. Self-reported attitudes are also susceptible to social-desirability effects, particularly regarding stated openness to innovation; the assurance of anonymity and the non-evaluative interview protocol were intended to mitigate, though they cannot eliminate, this tendency. The rapid pace of AI development means that attitudes documented here may have limited currency in the short term.

5.6. Future Research

Future research should broaden geographical coverage to test whether the knowledge-finance barrier dyad identified here is specific to this regional context or generalizes across Greek regions and comparable peripheral economies, particularly other Mediterranean peripheries where the biocultural reading developed here may be directly testable. Integrating quantitative methods would enable statistical correlation and comparative analysis. Longitudinal designs tracking SMEs through AI adoption cycles would capture dynamic shifts in capabilities, social capital formation, and employment outcomes. Research on the effects of AI on labour market skill requirements in peripheral regions, and on the

mediating role of local institutional intermediaries, would advance both theory and policy design for SDG-aligned regional development.

6. Conclusions

This study investigated the interplay between AI adoption, social capital formation, workforce dynamics, and sustainable development in the region of Eastern Macedonia and Thrace, one of the least developed regions in the European Union and an analytically significant case for the study of technology diffusion under conditions of peripheral disadvantage. Drawing on twelve semi-structured interviews with SME owners and managers, analysed thematically through Atlas.ti, the research addressed what factors influence AI acceptance among peripheral SMEs, how adoption barriers can be overcome, and what best practices exist for integrating AI into SME development strategies. From this single-region, small-sample qualitative base, the study advances four analytical propositions. They are offered for transfer and testing in comparable peripheral economies, not as findings generalizable to the SME population at large.

Start with the nature of the challenge. In peripheral SMEs, AI adoption is less a technological or financial problem than a social and human capital one. Knowledge deficits, network atrophy, risk aversion, and dependence on outside partners are not signs of firms that have simply failed to adapt. They are symptoms of a socio-spatial disadvantage that compounds over time, as brain drain hollows out human capital and the loss of inter-firm trust reinforces it [10,11,23]. Sustainable AI adoption in weak peripheral regions does not begin with technology provision. It begins with the reconstruction of the social and human capital infrastructure (civic trust, inter-firm collaboration, and educational endowment) within which technology adoption becomes possible and sustainable.

External partnerships have their limits as an adoption mechanism. Bridging ties to outside technology providers replaces the absorptive capacity that peripheral SMEs lack [17,19], and that substitution is necessary. But when a partnership hands over technology without transferring knowledge or building internal capacity, it can deepen the very core–periphery dependency it was meant to solve. Partnerships work only when they are tied to knowledge transfer, peer learning, and the slow rebuilding of homegrown innovation capacity.

Whether AI advances or undermines SDGs 4, 8, 9, 10, and 17 depends less on the technology itself than on the social and institutional environment in which adoption occurs. Where targeted investment in digital literacy (SDG 4), active labour market policy (SDG 8), social and institutional innovation infrastructure (SDG 9), redistributive regional policy (SDG 10), and capacity-building partnership frameworks (SDG 17) are absent, AI adoption in regions such as EMT is more likely to reproduce and deepen existing spatial inequalities than to contribute to sustainable and inclusive development.

The last point is theoretical. Reading the case through Bitsani's [11] framework shows what a Mediterranean-specific lens can add to the study of peripheral disadvantage. Broad accounts of regional innovation systems [10] and uneven geographical development [9] describe how sparse peripheral innovation ecosystems are. What they miss are the culturally and historically specific forces, eroding civic trust, institutional dependency, and the particular shape of Mediterranean brain drain, that steer adoption in regions such as EMT. Bringing culturally grounded approaches into the AI adoption literature is a promising line for future theory, and for designing policies that reach the full depth of regional disadvantage instead of only its visible technological and financial surface.

Author Contributions: Conceptualization, E.P.B., V.K. and A.K.; methodology, V.K. and T.G.; software, V.K. and T.G.; formal analysis, V.K., T.G. and A.K.; investigation, V.K. and T.G.; writing—original draft preparation, E.P.B., V.K. and A.K.; writing—review and editing, E.P.B., V.K., T.G., A.K. and S.P.;

supervision, E.P.B.; project administration, E.P.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Ethics review and approval were not required for this study under Greek Law 4521/2018 (Article 23, as amended by Articles 277–282 of Law 4957/2022), which renders Research Ethics Committee approval mandatory only for externally funded projects involving research on human subjects, human-derived material, personal data, animals, or the natural and cultural environment. The present study received no external funding and consisted exclusively of semi-structured interviews with adult business owners and managers concerning their professional views on technology adoption, involving no medical procedures, biological samples, vulnerable populations, or interventions. Processing of personal data complied with Regulation (EU) 2016/679 (GDPR) and Greek Law 4624/2019. The study was conducted in accordance with the principles of the Declaration of Helsinki (1975, revised 2013).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are not publicly available due to privacy and confidentiality restrictions agreed with participants at the time of consent.

Acknowledgments: The authors thank the twelve SME owners and managers of Eastern Macedonia and Thrace who generously participated in this study.

Conflicts of Interest: The authors declare no conflicts of interest.

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